A STATISTICAL LEARNING APPPROACH TO VERTEBRA DETECTION AND SEGMENTATION FROM SPINAL MRI

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ABSTRACT

Automatically extracting vertebra regions from a spinal magnetic resonance image is normally required as the first step to an intelligent spinal MR image diagnosis system. In this work, we develop a fully automatic vertebra detection and segmentation method. Our system consists of three stages; namely, AdaBoost-based vertebra detection, detection refinement via robust curve fitting, and vertebra segmentation by an iterative normalized cut algorithm. We proposed an efficient and effective vertebra detector, which is trained by the improved AdaBoost algorithm, to locate the initial vertebra positions. Then, a robust estimation procedure is applied to fit all the vertebrae as a polynomial spinal curve to refine the vertebra detection results. Finally, an iterative segmentation algorithm based on normalized-cut energy minimization is applied to extract the precise vertebra regions from the detected windows. The experimental results show our system can achieve high accuracy on a number of testing 3D spinal MRI data sets.

Index Terms— Vertebra Detection, AdaBoost, RANSAC, Segmentation, Normalized-cut, spinal MR image

1. INTRODUCTION

An intelligent image understanding and diagnosis system has been the long-term goal of medical image analysis. With the increased use of diagnostic imaging, researchers from computer science and radiological engineering have endeavored to develop intelligent techniques to assist in both acquisition and diagnosis. Spine-related pathological change is commonly assessed with Magnetic Resonance (MR) imaging. An automatic technique of extracting vertebra regions from a spinal MR image could be the first step to an intelligent spinal MR image diagnosis application, such as automatic detection of spinal deformities and intervertebral disc disease. We present here a method for automatically detecting and then segmenting vertebrae from MR images.

Object detection is an important problem in computer vision research. In recent years, many different learning algorithms, such as eigen-space analysis [6], neural network [5], SVM [4], and AdaBoost [2] [11], have been proposed to solve this problem for different applications.

Traditional techniques for object localization from medical images are mostly based on simple image features and user interactions. Most systems were developed to assist the operators to achieve higher accuracy with minimal user interactions. Smyth et al. [3] adopted Active Shape Model (ASM) to locate vertebrae in Dual Energy X-ray Absorptiometry images, and the vertebra segmentation results provided by this algorithm are as good as those provided by manual operations. Wan and Higgins [9] focused on segmenting arterial trees from liver images. An initial interest point is necessary for their symmetric region growing algorithm. Reisman et al. [12] proposed a robust intervertebral disc location and orientation method with orientation map and local region analysis. In these systems, a simple user interaction to identify the approximate starting point or region is necessary.

Recently, some advanced techniques have been proposed to solve the object localization problem without user interactions. Brejl and Sonka [7] proposed a fully automated model-based segmentation method. Carballido-Gamio et al. [10] extended the normalized cuts segmentation method [8] to 3D spinal MRI segmentation.

In this paper, we present a fully automatic vertebra detection and segmentation system for spinal MRI. Our system consists of three stages; namely, AdaBoost-based vertebra detection, detection refinement via robust curve fitting, and vertebra segmentation by an iterative normalized cut algorithm. The experimental results show our system can achieve high accuracy in vertebra detection and segmentation on a number of testing spinal MRI data sets acquired with different types of MRI.

2. PROPOSED SYSTEM OVERVIEW

Our vertebra detection and segmentation system can be divided into four main components, which are depicted in the system flow diagram in Figure 1. In the training phase, we train an AdaBoost vertebra detector from a number of training vertebra images based on an improved AdaBoost algorithm. The execution part of the system includes the vertebra detection process, robust curve fitting process, and vertebra segmentation process.

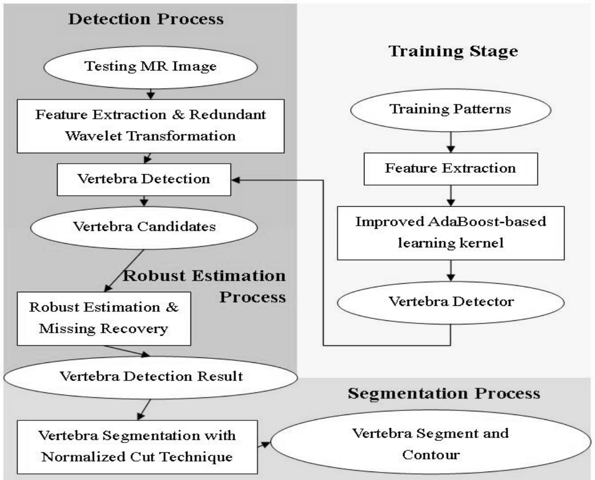


Fig. 1. Flow diagram of the proposed system

2.1. Training dataset and feature representation

The training data set was collected from 22 spinal MR image data sets. We manually labeled the vertebra regions and applied a minimal bounding rectangle to align the positive samples. After including slight rotations and shifts, there are a total of 9,786 positive training vertebra images in our training set. The negative training data are randomly selected 12x12 square images clipped from the non-vertebra parts of spinal MRI. The experimental dataset contains all three kinds of partial spines – cervical (C), thoracic (T) and lumbar (L) – as well as whole body scout images.

These positive and negative data sets are given to a 3-layered wavelet transformation procedure and the extracted 144-dimensional coefficients are applied to form the feature representation basis.

2.2. Paired Feature Learning System

The original AdaBoost algorithm [11] combined many simple binary weak classifiers to form a strong classifier. Later, several researchers modified this machine learning algorithm to strengthen its classification power or computational efficiency for different applications. In this work, we propose an improved AdaBoost-based learning system specialized for vertebra detection in MRI. Algorithm 1 gives whole the proposed learning algorithm with the details described in the following sections.

3. PROPOSED METHODS

In this section, we will describe the details of our proposed system. The novel design of the paired feature learning system based on an improved AdaBoost algorithm is described from 3.1 to 3.3. Then, the RANSAC robust estimation for false alarm elimination and missing recovery is described in 3.4. Finally, an iterative normalized-cut energy minimization method in 3.5 is applied to extract the vertebra contour to pixel-wise precision from a detected window.

Table 1. The proposed learning algorithm for vertebra detection

- Given example images $(x_1,y_1),\ldots,(x_n,y_n)$, where y_i takes the value 0 for negative examples or 1 for positive examples, respectively
- Initialize weights $w_{1,i} = 1/(2m)$ for $y_i = 0$ or $w_{1,i} = 1/(2l)$ for $y_i = 1$, where m and l denote the total numbers of negative and positive images, respectively.
- For $t = 1,\ldots,T$
  1. Apply the ID3-like balance tree quantization method to find the quantization function $f_j(x)$ which will try to separate positive and negative samples into different bins. (See section 3.1 for details.)
  2. Map all training samples onto all possible paired feature spaces $f_{j,k}(x_i)$, $i = 1,\ldots,n$, and estimate their distributions. (See section 3.2 for details.)
  3. Compute the conditional probability as the Bayesian classification result for each weak classifier $C_{j,k}(x)$. (See section 3.3 for details.)
  4. Estimate the error $\varepsilon_{j,k}$ for each feature pair (j,k) as follows:
     $$\varepsilon_{j,k} = \sum_{i=1}^{n} w_{t,i} \times | y_i - C_{j,k}(x_i) |$$
  5. Select the paired feature h(t) with minimum error $\varepsilon_{j,k}$
     $$h(t) = arg \min_{(j,k)} \varepsilon_{j,k}$$
  6. Update the weights for all training samples as follows:
     $$w_{t+1,i} = w_{t,i} \times \beta_t^{1-|y_i - c_{h(t)}(x_i)|}$$
     where $\beta_t = \varepsilon_{h(t)}/(1-\varepsilon_{h(t)})$.
  7. Normalize the weights by $w_{t+1,i} = \dfrac{w_{t+1,i}}{\sum_{i=1}^{n} w_{t+1,i}}$
- The final classifier is given by
  $$SC(x) = \begin{cases} \text{vertebra} & \text{when} \sum_{t=1}^{T} \alpha_t C_{h(t)}(x) \geq \frac{1}{2}\sum_{t=1}^{T}\alpha_t \\ \text{non-vertebra} & \text{otherwise} \end{cases}$$

where $\alpha_t = \log(1/\beta_t)$

3.1. ID3-like Quantization

This learning system starts with an ID3-like balance tree quantization for computing the discrete joint distributions between positive and negative images. This quantization for each feature is determined based on the distribution of the training data with current weight functions. Compared to other traditional discretization methods, our ID3-like approach can preserve more information with a little bit more computational effort. In the ID3-decision tree, the entropy and information gain are defined as follows:

$$\begin{aligned} Entropy\ (S) = & -p(y_i = 1 \mid x_i \in S, W_t) \log\ p(y_i = 1 \mid x_i \in S, W_t) \\ & - p(y_i = 0 \mid x_i \in S, W_t) \log\ p(y_i = 0 \mid x_i \in S, W_t) \end{aligned} \quad (1)$$

$$Gain\ (S, A) \equiv Entropy\ (S) - \sum_{v \in leaf\_nodes} \frac{|S_v|}{|S|} Entropy\ (S_v) \quad (2)$$

where W_t is the weighting function for each training sample We can select the best threshold value that maximizes the information gain. The ID-3 quantization procedure is accomplished by repeating this process recursively in the parent nodes, and therefore a quantization function $f_j(x)$ is determined.

3.2. Paired Feature Representation

Our original wavelet feature dimension is 144. Mapping all training data onto a paired feature space can increase the feature varieties dramatically. Thus, the total number of possible features is increased from 144 to 10296 without extracting any additional features. As the ID3-like quantization method preserves more information, the paired feature mapping can increase the discrimination capabilities with the same feature representation.

3.3. Bayesian Weak Classifiers

For each pair of features, we can train a weak classifier based on this paired plane. The AdaBoost training algorithm is then used to select some powerful "weak classifiers" and combines them to determine if the corresponding window belongs to a vertebral region. For each weak classifier, we apply the Bayesian decision rule to compute the conditional probability density function in each interval. Instead of a binary decision, our Bayesian weak classifiers can model the ratio between positive and negative samples to exploit more information. By applying the Bayes rule, we can compute the conditional probability as follows:

$$C_{j,k}(x_i) = \frac{p(y_i = 1 \mid f_{j,k}(x_i), W_t)}{p(y_i = 0 \mid f_{j,k}(x_i), W_t) + p(y_i = 1 \mid f_{j,k}(x_i), W_t)} \quad \textbf{(3)}$$
$$= \frac{p(f_{j,k}(x_i) \mid y_i = 1, W_t)}{p(f_{j,k}(x_i) \mid y_i = 1, W_t) + p(f_{j,k}(x_i) \mid y_i = 0, W_t) \cdot \frac{p(y_i = 0)}{p(y_i = 1)}}$$

Equation (3) returns a value between 0 and 1, which denotes the relevance conditional probability.

3.4. Robust Estimation for Spinal Curve Fitting

Robust Estimation can help us to eliminate outliers and recover the missed vertebrae by fitting the detection result to a trend curve through RANSAC. For a partial spine volume of only the cervical (C), thoracic (T) or lumbar (L) spine, the robust estimation produces a single quadratic curve.

After the spinal curve is estimated, the recovery of missed vertebra detections can be accomplished based on the assumption of approximately equal-spaced occurrences of vertebrae along the curve.

For a whole-spine MRI, we have prior information that can help to predict the locations of possibly missed vertebrae more precisely. The vertebra size becomes larger along the spinal curve for all the C, T, and L spine. So we add a small constant to present this gradually increasing phenomenon between each partial spine.

3.5. Vertebra Segmentation

The traditional normalized cut technique [8] was developed for graph partitioning, and can be solved by eigenvalue decomposition. In this work, we adopt the same formulation and proposed a novel iterative solution which can accurately provide the contour of the vertebra region.

In the graph theoretic framework, the optimal partition can be found by minimizing the cut value. Moreover, normalized cut incorporates the idea of balanced partition in the energy function to avoid leading to a biased grouping result. Shi and Malik [8] defined the disassociation measure as follows:

$$Ncut(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)} = \frac{\sum_{x_i>0,x_j<0} -w_{ij}x_ix_j}{\sum_{x_i>0} d_i} + \frac{\sum_{x_i<0,x_j>0} -w_{ij}x_ix_j}{\sum_{x_i<0} d_i} \quad \textbf{(4)}$$

where **x** is a |V|-dimensional vector with x_i set to 1 when node i belongs to group A and -1 otherwise. Note that $d_i = \Sigma_j w_{ij}$ is the sum of all connected edge weights from node i to all other nodes.

The normalized-cut minimization can be rewritten as:

$$\min_x Ncut(x) = \min_y \frac{y^T(D-W)y}{y^T Dy} = \max_y \frac{y^T Wy}{y^T Dy} \quad \textbf{(5)}$$

Note that equation (5) can be reformulated into (6)

$$\frac{y^T Wy}{y^T Dy} = \frac{(P^T + bN^T)W(P+bN)}{(P^T + bN^T)D(P+bN)} = \frac{P^T WP + 2bP^T WN + b^2 N^T WN}{P^T DP + 2bP^T DN + b^2 N^T DN} \quad \textbf{(6)}$$

where y = P+bN. The vector P_i is set to 1 when x_i is 1 and 0 otherwise. The vector N_i is set to -1 when x_i is -1 and 0 otherwise. The value b is given by $\sum_{x_i>0} d_i / \sum_{x_i<0} d_i$.

We can find the minimal solution for equation (6) in an iterative framework, thus leading to an iterative region growing and shrinking algorithm.

4. EXPERIMENTAL RESULTS

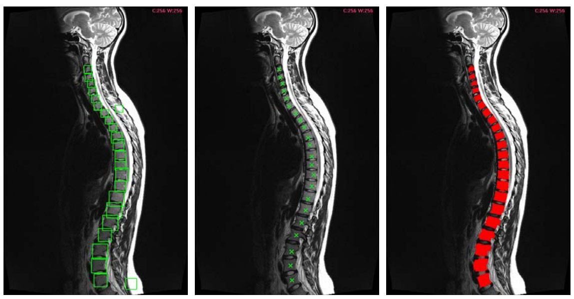
The first few experiments for our vertebra detection and segmentation system were performed on partial spinal MRI data sets, including C-spine, T-spine, and L-spine MR images. The vertebra classifier performs the detection on the Harr wavelet domain. Then, the robust spinal curve fitting is applied to eliminate the outliers and recover the missed vertebrae. The results are shown in Figure 2.

In Figure 2(a), the AdaBoost detector detected 8 vertebrae from the L-spine MR image, including 6 correct detections and 2 false alarms. These false alarms appear at the back bone because of the similarity in the wavelet gradient domain. After the refinement process through robust curve fitting, these false alarms were all eliminated as shown in Figure 2(b). Figure 2(c) illustrates the segmentation results.

We also tested the proposed vertebra detection algorithm on the whole-body MRI. The detection results after applying the AdaBoost detector and the subsequent refinement process with robust curve fitting are shown in figure 3. It is evident that the proposed vertebra detector successfully detected all the vertebrae without any false alarm after the refinement process in this example.

(a) (b) (c)

Fig. 2. Vertebra detection results for the C-spine MRI after (a) AdaBoost vertebra detector, (b) the refinement process with robust curve fitting, and (c) the normalized-cut segmentation.



(a) (b) (c)

Fig. 3. Experimental result of the whole-body scout MRI after (a) AdaBoost vertebra detector, (b) the refinement process with robust curve fitting, and (c) the normalized-cut segmentation.

The quantitative performance assessment of the proposed vertebra detection algorithm was performed on 17 spinal MR data sets. The detection results after the AdaBoost detector and the refinement process with robust curve fitting are summarized in Table 2. It is obvious that the refinement process significantly improves the detection accuracy of our vertebra detection algorithm.

Table 2: The accuracy and false positive of automatic vertebra detection result both before and after RANSAC (the latter shown in parentheses).

MRI Volume Type (No. of Data Set)	No. of Detected Vertebrae (RANSAC)	No. of Ground Truth	Detection Rate (RANSAC)	No. of False Positives (RANSAC)
C-spine (5)	42 (46)	47	0.8936 (0.9787)	20 (0)
T-spine (2)	14 (16)	16	0.8750 (1.000)	3 (0)
L-spine (8)	52 (53)	54	0.9630 (0.9815)	12 (0)
Whole-body (2)	42 (44)	45	0.9333 (0.9778)	8 (0)

The execution time of the proposed vertebra detection and segmentation algorithm depends on the size of the MR image. For an MR image of size 384-by-384, it takes less than one second. For the whole-body scout image of size 513-by-805, our program takes less than 4 seconds. Our experiments were tested on a Pentium-4 3.0G single core PC with 1G DDR RAM.

5. CONCLUSIONS

In this paper, we presented a fully automatic vertebra detection and segmentation algorithm for spinal magnetic resonance (MR) images. A machine learning approach based on an improved AdaBoost algorithm is proposed to detect the vertebra candidates. This type of object detection algorithm for medical images is efficient and effective. Our proposed method is proven to be more accurate than the original AdaBoost algorithm [2][11] with the same weak classifier setting.

The robust estimation technique is applied to verify the candidates by applying RANSAC [1] to fit a spinal curve to the detected vertebra locations, thus allowing the elimination of false alarms and recovery of missed detections. The experiments show that 98% of vertebrae can be correctly identified and most false alarms are eliminated in our datasets, including four different types of spinal MR images.

A novel iterative normalized-cut energy minimization process was developed for refined vertebra segmentation. This iterative method can effectively alleviate the high computational cost required in the original normalized cut segmentation [8].

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